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Interim monitoring of cost dynamics for publicly supported energy technologies

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ABSTRACT

The combination of substantial public funding of nascent energy technologies and recent increases in the costs of those that have been most heavily supported has raised questions about whether policy makers should sustain, alter, enhance, or terminate such programs. This paper uses experience curves for photovoltaics (PV) and wind to (1) estimate ranges of costs for these public programs and (2) introduce new ways of evaluating recent cost dynamics. For both technology cases, the estimated costs of the subsidies required to reach targets are sensitive to the choice of time period on which cost projections are based. The variation in the discounted social cost of subsidies exceeds an order of magnitude. Vigilance is required to avoid the very expensive outcomes contained within these distributions of social costs. Two measures of the significance of recent deviations are introduced. Both indicate that wind costs are within the expected range of prior forecasts but that PV costs are not. The magnitude of the public funds involved in these programs heightens the need for better analytical tools with which to monitor and evaluate cost dynamics.

1. Introduction

Large programs and deviations from trends in cost reductions are challenging policy makers to make decisions about whether, when, and how much to stimulate the development of energy technologies that have high external benefits. The net benefits of subsidies and other incentives programs depend heavily on the extent to which technologies improve over time. Experience curves provide a way for policy makers to incorporate technology dynamics into decisions that involve the future costs of technologies. They are now used widely to inform decisions that involve billions, and even trillions, of dollars in public funding. The general notion that learning from experience leads to cost reductions and performance improvements is well supported by a large array of empirical studies across a variety of technologies. But the appropriateness of using experience curves to guide policy is less uniformly acknowledged. Despite caveats in previous work, the cost projections that result from experience curves are typically used without characterizing uncertainty in those estimates.

The motivating premise behind this study is that rigorous analysis of the uncertainty involved in making experience curve-based cost projections can inform policy decisions and improve the outcomes of technology subsidy programs. Without better analytical tools, decisions about these programs are vulnerable to political expediency and near-term fiscal constraints. The use of the term interim monitoring here is meant to suggest the evaluation of data available between the time at which programs have begun and when the full benefits of cost reductions are expected to arrive. Because a substantial portion of the benefits of these programs arrive several years hence, monitoring the progress of technology cost reductions in the intermediate term is crucial for decision-making. Possible responses to interim results include: continuation of existing programs, early termination, changes to subsidy levels, and supplementing subsidies with complementary programs that address additional market failures and barriers. This study examines two questions: How sensitive are the social costs of subsidy programs to this uncertainty? And does characterization of uncertainty allow interpretation of the significance of apparent deviations from projections?

The dynamic characteristic of experience curves has provided a substantial advance over alternative models, which have tended to treat technology statically, or have assigned constant rates of change. The rate and direction of future technological change in energy technologies are important sources of uncertainty in models that assess the costs of stabilizing the climate (Edenhofer

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et al., 2006). Treatment of technology dynamics in integrated assessment models has become increasingly sophisticated (Grubb et al., 2002) as models have incorporated lessons from the economics of innovation and as increased processing power and improved algorithms have enabled optimization of phenomena, such as increasing returns, which in the past had made computation unwieldy (Messner, 1997). Yet the representation of technological change in large energy-economic model remains highly stylized relative to the state-of-the-art of understanding about the economics of innovation (Nordhaus, 2002). Perhaps one reason for the lag between the research frontier for the economics of innovation and that for the modeling of it has to do with incompatibilities in the methodological approaches of the two fields. On the one hand, research on the economics of innovation has tended to emphasize uncertainty (Freeman and Louca, 2001), cumulativeness (Rosenberg, 1994), and non-ergodicity (Arthur, 2006). The outcomes of this line of inquiry, which dates back to Schumpeter (1934), and even Marx (1867), have often been characterized by richness of description, a case study approach, and arguably, more progress with rigorous empirical observation than with strong theoretical claims. On the other hand, optimization and simulation models require compact quantitative estimation of parameters, with uncertainties that do not become effectively infinite once propagated through the model. One of the few concepts that has bridged the epistemological gap between the economics of innovation and the integrated assessment of climate change is the experience curve. Experience curves provide a way to project future costs conditional on the cumulative quantity of capacity produced. The resulting cost predictions are less deterministic than those generated by temporal-based rates of technological change, but they are also not simply scenarios, internally consistent descriptions of one possible future state of technology; they are conditional predictions.

The following section discusses the reasons for using experience curves, their prevalence, and the way that experience curve-derived cost projections are used in policy decisions. In Section 3 a stylized model is described for calculating the cost of a subsidy program. Section 4 presents the range of values that result from applying the model to two case studies, photovoltaics (PV) and wind power. Section 5 introduces two approaches to compare recent deviations to historical ex ante predictions. Finally, in Section 6 the implications of applying the results of this type of model to policy decisions are discussed.

2. Using experience curves for technology policy

Despite ample evidence of technological learning, the weak reliability of experience curve projections makes their application to inform policy decisions subject to strong caveats.

2.1. A wide array of technologies demonstrate "learning"

Experience curves have been assembled for a wide range of technologies. While there is wide variation in the observed rates of "learning", studies do provide evidence that costs, almost always, decline as cumulative production increases (Wright, 1936; Alchian, 1963; Rapping, 1965; Dutton and Thomas, 1984). The roots of these micro-level observations can be traced back to early economic theories about the importance of the relationship between specialization and trade, which were based in part on individuals developing expertise over time (Smith, 1776). The notion of the *experience curve* varies from the more specific formulation behind the learning curve in that it aggregates from individuals to entire industries, and from labor costs to all manufacturing costs.[1]

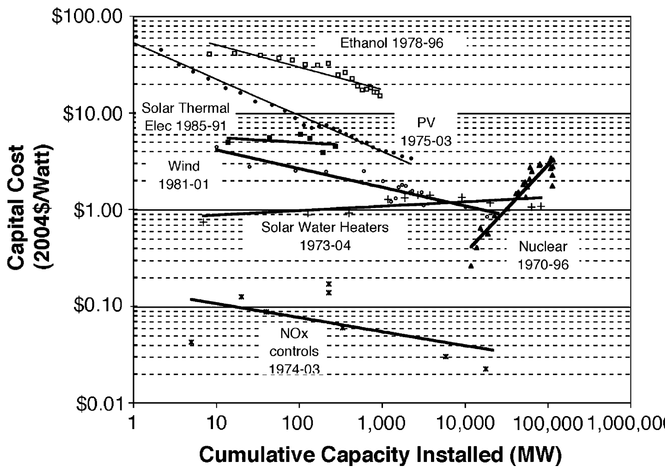

Fig. 1. Experience curves for energy technologies. Data from Nemet (2007).

Experience curves have been assembled for a wide variety of energy technologies. For useful studies and surveys see Wene (2000), McDonald and Schrattenholzer (2001), Junginger et al. (2005), Albrecht (2007), Hultman and Koomey (2007), and Neij (2008). Fig. 1 shows learning rates (LRs) for a variety of energy-related technologies.[2] The rates vary, but, with the exception of nuclear power and solar hot water heaters, costs do appear to decline with cumulative capacity. The dispersion in LRs included in these studies is attributable two factors: differences in how fast technologies "learn" and to omitted variable bias; exogenous technical improvements, changes in quality, and the price of input materials, all affect costs over time, and are not included in the cumulative capacity variable on the horizontal axis (Nemet, 2006). Still, perhaps because of a dearth of better tools, the experience curve persists as powerful tool for guiding policy decisions about the costs of future energy technologies.

2.2. Experience curves used to inform policy decisions

Experience curves are now used widely to inform decisions that involve billions of dollars in public funds. They have been used both directly—as graphical exhibits to inform debates—and indirectly, as inputs to energy-economic models that simulate the cost of achieving environmental goals. Much of the early work to translate the insights from experience curve studies to energy policy decisions is included in a study for the International Energy Agency (Wene, 2000). Other studies have used the tool directly to make claims about policy implications (Duke and Kammen, 1999; van der Zwaan and Rabl, 2004).

Energy-economic models that minimize the cost of energy supply now also include experience curve relationships to include technology dynamics. Model comparison studies have found that models' estimates of the social costs of policy are sensitive to how technological change is characterized (Edenhofer et al., 2006). Working Group III of the Intergovernmental Panel on Climate Change (IPCC) used results from a variety of energy-economic models to estimate the magnitude of economically available

[1] The technological "learning" used in the literature on experience curves refers to a broad set of improvements in the cost and performance of technologies, not strictly to the more precise notion of learning by doing, e.g. Arrow (1962).

[2] The data for ethanol are in units of dollars per gallon, rather than dollars per watt. For insight into why the cost of nuclear power increased, see Hultman et al. (2007).